Development of Hybrid Knowledge Modeling Tools for Smart Decision Making

A
SYNOPSIS

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INTRODUCTION

Decision making is very important, yet a complex task in the present information age as it requires properly structuring the problem, evaluating multiple and often conflicting criteria, and considering variability, interdependency and uncertainty of the factors that affect the decision making process. These complexities compel the decision maker to utilize different methods and tools for supporting the decision analysis. The focus of researchers has been on providing several decision making tools (Mardani et al., 2015; Fdhila, Indion, Rinderle-Ma & Vetschera, 2017; Osei-Bryson, 2018; Guarini, Battisti & Chiovitti, 2018; Koo, Chun & Griffith, 2018; and Roberts & Kovacich, 2018) to assist the decision makers in their decision making process.

Decision support system (DSS) is an interactive computerized system intended to provide support to the decision maker engaged in solving various semi-structured or un-structured problems. It conveys the decision support information through synthesis and interpretation of quantifiable and scientific data.

The DSS plays a vital role in the situations where:

- decisions involve large amount of data and complex processing;
- decision making involves uncertainties;
- decisions includes multiple attributes, objectives, and goals; and
- precision and optimization is important.

A DSS couples decision analysis and optimization models to enhance the information access and retrieval functions with support for model building and model-based reasoning. This helps in making effective decisions that involve optimizing trade-offs on one hand; and also in dealing with human cognitive deficiencies on the other hand, by providing intelligent access to relevant knowledge, and aiding the process of structuring decisions.

Knowledge Management

Decision Support Systems have been frequently linked with knowledge management to enable a decision maker arrive at a more informed and scientific decision (Bolloju, Khalifa & Turban, 2002; Jones, 2006; Alyoubi, 2015). Knowledge management is the systematic underpinning, observatism, measurement and optimization of the domain knowledge. Knowledge management research focuses on the development of concept and tools for extracting knowledge, capturing its meaning, and making it available to the decision maker.

The main activities in knowledge management are:

1. **Acquisition**: This is identifying knowledge in the external environment of an organization and transforming it into a representation that can be employed by the organization.
2. **Selection**: This refers to identifying needed knowledge within existing knowledge resources of the organization and providing it in an appropriate representation to an activity that needs it.
3. **Generation**: Generation means producing knowledge by discovering, or deriving it from existing knowledge.
4. **Assimilation**: This involves storage and/or distribution of acquired, selected and/or generated knowledge within the organization.
5. **Emission**: Emission is using existing knowledge to produce organizational outputs for release into the environment.

The knowledge management process is shown in Figure 1.

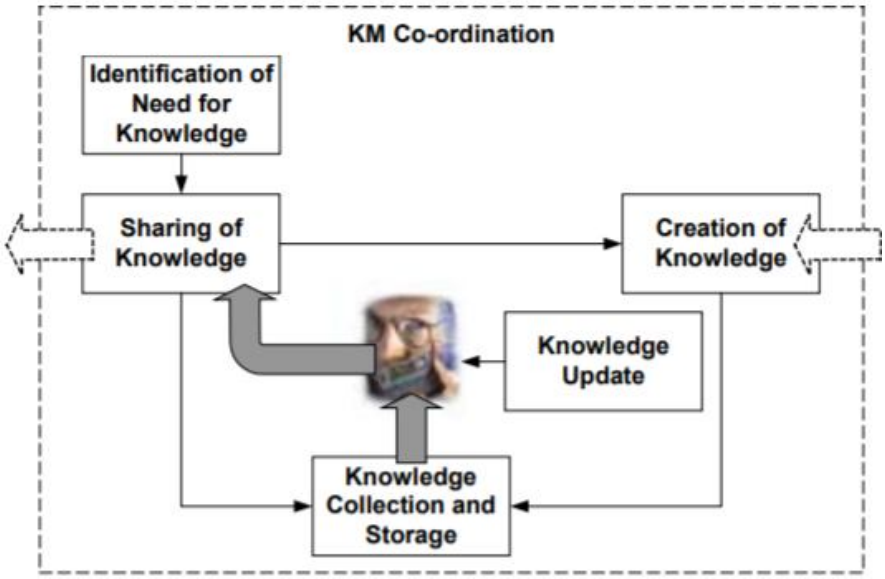

Figure 1: Knowledge Management Process (Kucza, 2001)

Knowledge Management is the practice of capturing tactic knowledge and converting it to explicit knowledge. Both tacit and explicit knowledge can be managed by using a knowledge management system, which is a specialised system that interacts with the organization's systems to facilitate all aspects of knowledge processing. A knowledge management system is developed using knowledge engineering techniques. Knowledge engineering encompasses methods and techniques for knowledge acquisition, modelling, representation and use of knowledge (Schreiber et al., 1999).

A. Knowledge acquisition

Acquiring knowledge, or knowledge discovery, refers to the process of analyzing large amounts of data with the aim of discovering new information and knowledge, and its application in resolving business problems. More specifically, it refers to mining data as the initial step of this process using data-driven learning algorithms, with the aim of discovering correlations between them. Knowledge acquisition techniques can be grouped into three categories: manual, semi-automated (interactive) and automated (data mining), and can be performed in various ways as shown in Figure 2.

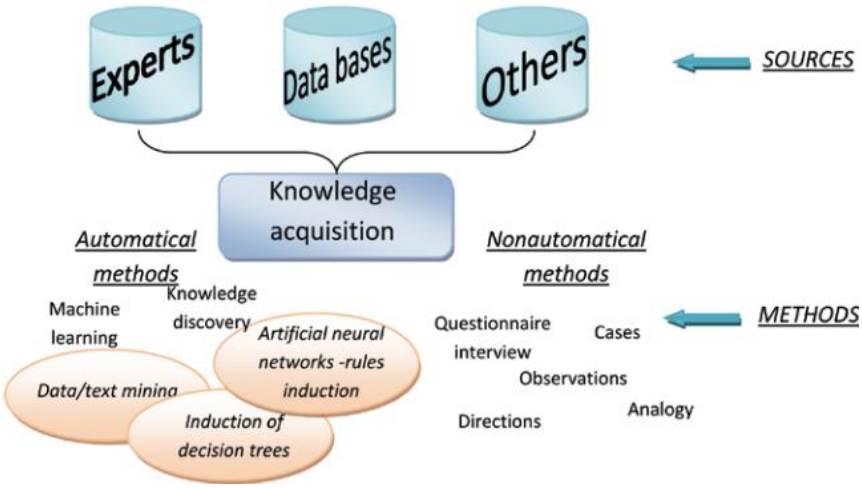

Figure 2: Methods of knowledge acquisition (Gajzler, 2010)

Data Mining

Data mining, a knowledge discovery technique, looks for hidden, valid, and potentially useful patterns in huge data sets. It helps in discovering unsuspected or previously unknown relationships amongst the data. Data mining is a multi-disciplinary skill that uses machine learning, statistics, artificial intelligence and database technology. Data mining can be achieved by:

a. *Association*: In Association, the relationship of a particular item in a data transaction on other items in the same transaction is used to predict patterns.

b. *Classification:* In Classification, the methods are intended for learning different functions that map each item of the selected data into one of a predefined set of classes. Given the set of predefined classes, a number of attributes, and a *learning* (or *training*) *set*, the classification methods can automatically predict the class of other unclassified data of the learning set.

c. *Cluster analysis:* Cluster analysis takes ungrouped data and uses automatic techniques to put this data into groups. Clustering is unsupervised, and does not require a learning set. It shares a common methodological ground with Classification.

d. *Prediction analysis:* The key idea of prediction analysis is to discover the relationship between the dependent and independent variables, and the relationship between the independent variables.

e. *Sequential Pattern analysis:* Sequential Pattern analysis seeks to find similar patterns in data transaction over a business period. These patterns can be used by business analysts to identify relationships among data.

f. *Similar Time Sequences:* Similar Time Sequences are applied to discover sequences similar to a known sequence over both past and current business periods. Several similar sequences can be studied in the data mining stage to identify future trends in transaction development. This approach is useful in dealing with databases that have time-series characteristics.

Data mining and Linked open Data

The concept of Linked open data is about the *linking of all publically accessible data* together (Heath and Bizer, 2011) and has been recognized as a valuable source of background knowledge in many data mining tasks (Paulheim & Fümkranz, 2012; Lausch, Schmidt & Tischendorf, 2015). Data-mining methods can extract patterns and knowledge only from closed data sets, where all of the data required for the analysis are associated through known relationships as established in relational databases. Consequently, it is the job of the analyst to couple all of the necessary data and information that could potentially influence patterns and processes. Hence, it is possible that new or unknown patterns and knowledge are not recorded due to incorrect decisions that have been made previously.

Linked open data, a new data mining approach, is a recent development whereby all data sets, freely available on the Internet, are linked and interrelated by way of semantic nets and techniques (Dengel, 2012). This inter-linked data can be understood by determining a number of rules about these relationships, which enables global data mining approaches and the discovery of truly new associations, patterns and knowledge. Linked Open Data can not only add categorical information which allows for an easier exploration of results, but additional visual clues can also be added.

Spatial Data mining

The explosive growth of spatial data and widespread use of spatial databases emphasize the need for the automated discovery of spatial knowledge. Extracting useful patterns from spatial datasets is a difficult task due to the complexity of spatial data types, spatial relationships, and spatial autocorrelation. Spatial Data Mining is the process of discovering interesting and previously unknown, but potentially useful patterns from large spatial datasets. More on spatial data mining can be found in Perumal, Velumani, Sadhasivam & Ramaswamy (2015), and Asmita & Mainaz (2017). Hwang (2004), Refonaa, Lakshmi & Vivek (2015), Goudarzi & Ghadiri (2017), and Goyal, Sharma & Joshi (2017) have developed various tools for spatial data mining.

The explicit location and extension of spatial objects define implicit relations of spatial neighborhood (such as topological distance, and direction relations) which are used by spatial data mining algorithms. The spatial predicates and relationships for a set of spatial data are materialized using thematic layers. Each layer contains data about a specific kind of spatial data (that is having a specific theme) for example parks and recreation areas data. The spatial materialization could be performed as preprocessing steps before the application of data mining techniques or it could be perform as an intermediate step in spatial mining (Figure 3).

B. Knowledge Modeling

Knowledge Modeling can be considered as an exploratory process involving the application of various algorithmic procedures for manipulating data, building models from data, and manipulating the models. Knowledge modeling approach (a) enables the knowledge to be re-used in different areas of the same domain, (b) helps in developing knowledge system that can interact with other systems in the organization, and (c) results in reducing development costs.

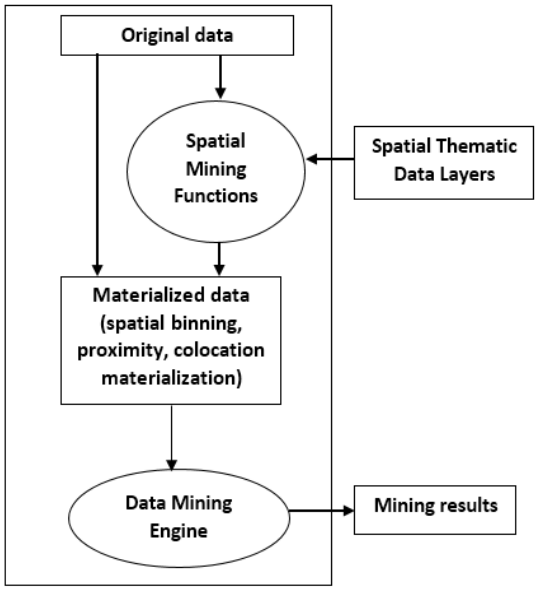

Figure 3: Spatial Data Mining Process

Knowledge Modeling is viewed as a top-down process where an abstract model is selected or constructed which is then instantiated with application-specific knowledge. The modeling process constructs conceptual models of acquired knowledge, which often is unstructured and is in tacit form. Knowledge modeling contributes to the understanding of the source of knowledge, the inputs and outputs, the flow of knowledge, and the identification of other variables such as the impact that management action has on the organizational knowledge (Davenport and Prusak, 1998). Thus knowledge modeling has become an important aspect in the process of building knowledge management systems. Understanding and selecting the modeling technique that is appropriate for different domains of knowledge will ensure the success of the knowledge management system being designed.

Ontology

Ontology is a knowledge modeling scheme that provides a common vocabulary for representation of domain knowledge. Ontology is a *specification of a conceptualization* (Gruber, 1995). Ontologies can be

classified according to two dimensions: the amount and type of structure of the conceptualization and the subject of the conceptualization. On the basis of structure, the ontologies can be categorized as:

a. *Terminological ontologies:* These specify the terms that are used to represent knowledge in the domain of discourse, such as lexicons;
b. *Information ontologies:* These specify the record structure of databases. Example includes conceptual schemata of databases; and
c. *Knowledge modeling ontologies:* These ontologies specify conceptualizations of the knowledge, and have a richer internal structure.

On the basis of subject of the conceptualization, ontology can be categorized as:

i. *Application ontologies:* Application ontologies contain all the definitions that are needed to model the knowledge required for a particular application. These are a mix of concepts that are taken from domain ontologies and from generic ontologies. Application ontologies are not reusable themselves.
ii. *Domain ontologies:* These ontologies express conceptualizations that are specific for particular domains. The domain ontology puts constraints on the structure and contents of domain knowledge.
iii. *Generic ontologies:* These are similar to domain ontologies, but the concepts that they define are considered to be generic across many fields. The concepts in domain ontologies are often defined as specializations of concepts in generic ontologies.
iv. *Representation ontologies:* Representation ontologies explicate the conceptualizations that underlie knowledge representation formalisms. These provide a representational framework without making claims about the world.

The two key elements of ontology are concepts and relationship. *Concepts* stand for the abstractive components of a domain and are represented by classes. *Relationship* is the linkage between different concepts (or between concepts and end data) and is represented by properties of the classes. The advantages of ontology include:

- *Knowledge sharing*: Ontology can be used for sharing and communicating information among different applications since it has the capability to represent common understanding of a domain (Barbau et al., 2012).
- *Knowledge retrieval*: Ontology can be used to build the reference network for retrieval since it has the capability to represent complex relations among concepts (Li, Qin, Gao & Qin, 2014).
- *Knowledge documentation and reuse*: Ontology can be used to capture and document specific information since it provides an instance generation or documentation mechanism (Chang, Rai & Terpenny, 2007).

Researchers have developed different methods of knowledge modeling using ontologies (Chan, 2004; Xu, Cai & Chen, 2012; Panagiotopoulos, Kalou, Pierrakeas & Kameas, 2012; Lu, Li, Zhou & Deng, 2015; Zhang, Wang, Li & Jiang, 2017; Konys, 2018). Ontology has also been combined with knowledge generation methods by Zheng & Li (2008), Li, Thomas & Osei-Bryson (2017), and Bilal, Pornpit & Kit (2018) for intelligent knowledge retrieval.

Ontologies are increasingly seen as a key technology for enabling semantics driven knowledge processing. Communities establish ontologies, or shared conceptual models, to provide a framework for sharing a precise meaning of symbols exchanged during communication. Next-generation knowledge management systems will likely rely on conceptual models in the form of ontologies to precisely define the meaning of various symbols.

C. Knowledge Visualization

Knowledge visualization, another essential part knowledge management, transfers and creates new knowledge through using visualizations. The transfer of knowledge is a core process in knowledge management which can be improved by using visual representations. Knowledge visualization is a field of study that investigates the power of visual formats to represent knowledge. It aims at supporting cognitive

processes in generating, representing, structuring, retrieving, sharing, and using knowledge (Tergan, 2005). The process of Knowledge Visualization contains steps such as gathering, interpreting, developing an understanding, organizing, designing, and communicating the information. The area of Knowledge Visualization develops cutting-edge visualization methods for analyzing large amounts of data and helping users understand complex relationships between them. By combining interactive visualization with automatic analysis, the discovery of unexpected phenomena, verification of known facts and deriving of new knowledge out of massive data is facilitated.

For an effective transfer and the creation of knowledge through visualizations, which forms the Knowledge Visualization Framework, four perspectives should be considered (Burkhard, 2005):

- *Function Type Perspective*: helps in visualizing the aim;
- *Knowledge Type Perspective*: clarifies the nature of the content;
- *Recipient Type Perspective*: points to the different backgrounds of recipient audience; and
- *Visualization Type Perspective*: structures the main visualization types according to their individual characteristics.

Semantic Network

The semantic network is an attempt to make the knowledge representation close to a form in which it can supposedly be stored in human memory. The simplest kind of semantic network is a relational graph consisting of triplets of the *subject–predicate–obje*ct form. Chains of triplets form a network whose graph makes it possible to represent the meaning of fairly complex concepts.

A semantic network (or semantic net) is a knowledge representation technique used for propositional information. Mathematically a semantic net can be defined as a labeled directed graph.

Semantic nets consist of nodes, links (edges) and link labels. In the semantic network diagram, nodes appear as circles, ellipses or rectangles to represent objects (such as physical objects, concepts or situations). Links appear as arrows to express the relationships between objects, and link labels specify particular relations. Relationships provide the basic structure for organizing knowledge. The semantic network:

- allows inheritance reasoning, multiple inheritance, and inverse links;
- have the ability to represent default values for categories;
- convey some meaning in a transparent manner;
- are simple and easy to understand; and
- are easy to translate into PROLOG.

Literature Review

Researchers are continuously developing new concepts, and tools for improving the decision making tasks. Decision support system (DSS), an efficient decision making tool, helps decision makers to take a rational decision for complex problems. These systems have been widely developed in various areas of decision making. Guo & Lim (2012) designed and implemented a decision support for online group negotiation and presented its theoretical foundation. Accorsi, Manzini & Maranesi (2014) presented a DSS for the design, management, and control of warehousing systems by implementing a top-down methodology that considers operative operations management. In the 21st century, the advances in Information Technology has brought the era of integrated decision support applications.

The multi-criteria decision support systems integrate multi-criteria decision making (MCDM) techniques with DSS. Martins, López, de Almeida, Almeida & Bortoluzzi (2017) developed a web-based DSS integrated with MCDM to analyze the impacts of portfolio size in a project portfolio selection for an electricity company in Brazil. Mir & Padma (2017) proposed a fuzzy based multi-criteria DSS to evaluate and prioritize critical success factors for the development of agricultural DSS and provided an estimate of weightings, which measures the relative importance of these factors under generic multi-criteria settings. Dolan & Veazie (2018) compared decision-making processes and outcomes of patient-level analyses with a range of multicriteria methods that vary in intensity of decision support. Farshidi, Jansen, de Jong & Brinkkemper (2018) presented a multi-criteria DSS that supports decision-makers in choosing the most suitable database technology. Nikas, Doukas & López (2018) developed a Multiple Alternatives-Criteria-Experts DSS to assess how multiple criteria decision analysis can bridge the gap between climate policy studies and experts. Yanie et al. (2018) applied a MCDM method, the ELECTRE method, in a web based DSS for developing a fast ranking process.

Web technology has provided an effective means of delivering and sharing decision support functionalities. Ocalir-Akunal (2016) developed a web based DSS for individuals' travel alternatives between any origin and destination points in urban areas. The Floyd-Warshall algorithm was used to solve all-pairs shortest path problem. Mladineo, Mladineo & Knezic (2017) described a Multi-Criteria-Analysis based web DSS developed for the management of incidents in maritime traffic. The developed DSS helps to organize a large quantity of information related to emergency management, spatial data and *live* data (radar data, weather forecasting data). Abdulllah, Alqulaity & Bajaber (2018) documented the evolvement of web-based DSS and the impact of the web analysis on DSS. Kantartzis & Malesios (2018) developed a web DSS, online Forest Road Management Platform, to assist in the management of forest road network and proposed a methodology using geoprocessing and geospatial technologies for visualization of forest roads, and the optimization of the management of the forest road network. Soyemi & Bolaji (2018) designed a framework to assist farmers increase their productivity by receiving weather information through a web-based DSS. The application uses Short Message Service (SMS) Technology for disseminating weather forecasting to farmers according to their eWarning setup. Van Cauwenbergh, Ballester Ciuró & Ahlers (2018) aimed at improving water management in a highly agricultural productive, and heavily water-stressed basin, the southern Spanish Andarax river basin, by developing a web-based spatial DSS.

A Spatial DSS is an interactive, computer-based system designed to solve a semi-structured spatial problem that integrates geographic information system with DSS. Elhag (2014) developed a remotely sensed vegetation indices and spatial DSS for better water consumption Regime in Nile Delta. Jankowski, Fraley & Pebesma (2014) presented a decision support approach to solve problems characterized by spatially-explicit decision variables, multiple objectives, and preferences for ancillary decision criteria. The approach offers a three-step workflow, in which Pareto non-dominated solutions are generated with a spatially adaptive genetic algorithm, and objective value trade-offs are examined in an interactive graphics environment. Horita, de Albuquerque, Degrossi, Mendiondo & Ueyama (2015) presented a Spatial DSS for flood risk management. The work was deployed in a real scenario of flood risk management in the town of

São Carlos in Brazil. Jelokhani-Niaraki & Malczewski (2015) presented a Web-based spatial DSS for selecting a parking site in Tehran. A web-based Spatial DSS was implemented by Wanderer & Herle (2015) for identifying locations for solar power plants based on user preferences. A spatial DSS was constructed by Escalante, Castro, Gauthier-Maradei & De La Vega (2016) to identify the most suitable location for biogas facilities, and determine optimum plant capacity. The tool was validated on seven crop residues located in Santander, Colombia. Ferretti & Montibeller (2016) discussed the key challenges and the associated meta-choices in spatial DSS**.** Irfan, Koj, Sedighi & Thomas (2017) presented an integrated and generic Spatial DSS by integrating artificial intelligence and multi-criteria decision analysis techniques to address commonly faced spatial decision problems of site selection, site ranking, impact assessment and spatial knowledge discovery under one system. Lombardi, Abastante, Torabi Moghadam & Toniolo (2017) presented a multi criteria SDSS to identify and evaluate alternative energy urban scenarios in a long-term period perspective. Balogun, Matori & Kiak (2018) developed a Spatial DSS by utilizing analytic hierarchy process to perform tradeoffs in determining the most significant resources to be secured considering the limited resources and time available to perform the response operation. Konstantinos, Georgios, Garyfallos, Zacharoula & Eleni (2018) presented a Spatial DSS to locate the most suitable areas for biomass power plant installation using fuzzy logic. Mileu & Queirós (2018) presented a knowledge based spatial DSS to assist spatial planning by integrating the risk management component at municipal level by using a semi-quantitative risk assessment.

Knowledge-Based DSS have evolved greatly over the last few decades. The concepts of Knowledge-Based DSS can be found in Fiannaca, La Rosa, Urso, Rizzo & Gaglio (2013); Ngai, Peng, Alexander & Moon (2014); Liu & Zaraté (2014); and Zaraté & Liu (2016). Zhuang, Wilkin & Ceglowski (2013) designed a framework for an intelligent DSS in the context of pathology test ordering by general practitioners. The framework provides effective guidance for the practitioners. Bourouis, Feham, Hossain & Zhang (2014) presented a Smartphone based intelligent system integrated with microscopic lens that allows patients in remote and isolated areas for regular eye examinations and disease diagnosis. Fernandes, Vinagre & Cortez

(2015) proposed an Intelligent DSS that analyzes articles prior to their publication, using a broad set of extracted features (e.g., keywords, digital media content, and earlier popularity of news referenced in the article). A Hybrid DSS consisting of a simulator, a rule-based inference engine, and a knowledge-based system was developed by Sahebjamnia, Torabi & Mansouri (2017) to make an explicit trade-off analysis between cost efficiency and responsiveness of the designed humanitarian relief chains. Caroleo et al. (2018) described a knowledge-based DSS to improve the preparedness of crisis situations induced by natural and technological hazards. The decision model based on two MCDM algorithms follows a cascading effect simulation model. Ming et al. (2018) proposed a knowledge-based platform for decision support in the design of engineering systems. The system is built by modeling decision-related knowledge with templates using ontologies. Park, Yoon & Yoo (2018) proposed a knowledge-based intelligent DSS for operational risk management of global supply chains. The System predicts the supply chain performance using artificial neural network combined with particle swarm optimization. Sahu, Sahu & Sahu (2018) designed a knowledge based DSS for construction sectors, which can determine the status of the related supplier alternatives, and green supply chain measures.

Knowledge Management

The state of the world today demands better decision making from organizations which are based on facts about the current decision and information from past similar decisions. This can be done by capturing and sharing knowledge found within the organization. Thus the interest in the field of knowledge management is increased. Organizations are beginning to realize that in order to increase their competitiveness, they will need to practice the activities involved in knowledge management. Meihami & Meihami (2014), Cohen & Olsen (2015), Martín-de Castro (2015), Omotayo (2015), Abuaddous, Al Sokkar & Abualodous (2018), and Aziz, Bouazza, Jabur, Hassan & Al Aufi (2018) described knowledge management as an important tool in organizational management for facilitating knowledge sharing, and strategic thinking on the sustainability of corporate operations. The key technologies underpinning the knowledge management are knowledge acquisition, knowledge modeling, and knowledge visualization.

Knowledge Acquisition

Knowledge acquisition is concerned with deriving higher-level insights from data. Croitoru, Crooks, Radzikowski & Stefanidis (2013) presented a system prototype, GeoSocial Gaug, for harvesting, processing, modeling, and integrating heterogeneous social media feeds towards the generation of geo-social knowledge. Kuznetsov (2013) proposed an alternative to conceptual scaling for knowledge discovery in complex data. An unsupervised and incremental learning approach to the extraction of maritime movement patterns was presented by Pallotta, Vespe & Bryan (2013) for information supporting decisions. The proposed methodology, TREAD (Traffic Route Extraction and Anomaly Detection) was developed for different levels of intermittency, persistence and data sources. Chen, Tripathi & Mizuguchi (2016) upgraded and modeled data types in TargetMine relevant to drug discovery and development to enhance knowledge discovery. Ristoski & Paulheim (2016) presented a comprehensive overview of different stages of the knowledge discovery process. Authors demonstrated how linked open data can be used at various stages for building content-based recommender systems. Teufl et al. (2016) presented an overview of the current malware situation on smartphone platforms with a special focus on Android and used sophisticated knowledge discovery processes and lean statistical methods to analyze data. Wang, Chang, Li, Sheng & Chen (2016) proposed a novel feature selection method in which the hinge loss function is used to learn a sparse feature selection matrix for each learning task. Forkan, Khalil, Ibaida & Tari (2017) proposed a knowledge discovery based approach that allows the context-aware system to adapt its behavior in runtime by analyzing large amounts of data generated in ambient assisted living systems and stored in cloud repositories**.** Becerril-García & Aguado-López (2018) presented a semantic model for the selective discovery of knowledge about resources structured with the open archives initiative protocol for metadata harvesting. Bele, Panigrahi & Srivastava (2018) described how knowledge discovery is a frontier research issue of knowledge management and also proposed development of context specific corpus in the Hindi language.

Data mining

Data mining, an efficient method of business intelligence, is a process to extract knowledge from large scale data. Concepts of data mining can be found in Maksood & Achuthan (2016); Sethi, Malhotra & Verma (2016); and Vadim (2018). A survey on use of data mining techniques is presented in the domain of crime by Hassani, Huang, Silva & Ghodsi (2016), in the education domain by Nithya, Umamaheswari & Umadevi (2016), in engineering applications by Rogalewicz & Sika (2016), and in healthcare domain by Patel & Patel (2016).

Data mining has been used by authors to discover knowledge from different sources. Serapião & Bannwart (2013) focused on the use of data mining algorithms with rule and tree methods to identify flow patterns of vertical upward three-phase pipe flow. Shuliang, Gangyi & Ming (2013) discussed spatial data mining in the context of big data by elaborating the fact that spatial data plays a primary role in big data. Shahiri, Husain & Rashid (2015) developed prediction algorithm for identifying the most important attributes in a students' data using data mining techniques. Ozyirmidokuz, Uyar & Ozyirmidokuz (2015) extracted knowledge from an international firm's marketing channel to improve the efficiency of the marketing system and generated a decision tree model for predicting the marketing channel firms' complaints. Keerthana, Thamilselvan & Sathiaseelan (2016) concentrated on image classification technique to analyze the performance of image mining algorithms based on classification accuracy, processing time, error rates, sensitivity and specificity. Ren, Lv, Li, Zhou & Wang (2016) presented a data-mining platform based on cloud computing and concluded that this platform is highly scalable, has massive data processing capacities', is service-oriented, and has low hardware cost.

Abujayyab, Ahamad, Yahya, Ahmad & Aziz (2017) presented the automation of a spatial data-mining model for landfill site selection by integrating spatial programming environment (Python-ArcGIS) and non-spatial environment (MATLAB). Bendechache, Le-Khac & Kechadi (2017) proposed a new approach for Big Data mining and analysis that works on distributed datasets and deals with data clustering task of the

analysis. Gangappa, Mai & Sammulal (2017) analyzed different geographical location with spatial data mining techniques, and also provided an overview of the common knowledge discovery data mining methodologies in geographical location with spatial data mining. Goudarzi & Ghadiri (2017) presented a novel approach for spatial data mining based on the MOSES evolutionary framework which improves the classic genetic programming approach. Goyal, Sharma & Joshi (2017) introduced GIS, and spatial data mining issues and challenges, and role of spatial association rule mining in big data of GIS.

Spatial association rules were mined by Jayababu, Varma & Govardhan (2017) to automatic grouping of spatial data objects using a candidate generation process with three constraint measures: support, confidence, and lift. The proposed multiple kernel-based probabilistic clustering was applied to the associate vector for grouping the spatial data objects. Lagrab & Aknin (2017) presented the importance of spatial data mining and discussed multiple data sets preprocessing, classification functions, clustering and outlier detection in directions supervised learning for extracting classification rules and assessing the local amenity based on rules reliability. Schoier & Borruso (2017) presented the Modified Density-Based Spatial Clustering of Applications with Noise (MDBSCAN) algorithm and compared it with the classical k-means approach. Both applications used synthetic datasets and a dataset of satellite images. Vaswani & Karandikar (2017) presented an algorithm for Spatial Data Mining using Clustering. Wu, Wang, Liu & Xia (2017) provided a way to the economic operation and rational decision-making of power systems and gave the future development for the spatial data mining technology. Jatav & Sharma (2018) analyzed prediction systems for diabetes, kidney and liver disease using the data mining classification techniques, support vector machine and random forest. Kumar, Koushik & Sundar (2018) presented a review of machine learning and information digging techniques for digital investigation in interruption detection. Lashari, Ibrahim, Senan & Taujuddin (2018) investigated the existing prospects of medical data classification based on data mining techniques and highlighted major advanced classification approaches used to enhance classification accuracy. Nalini & Meera (2018) conducted a comparison between two algorithms using WEKA and analyzed classification accuracy and execution time and various other parameters.

Knowledge Modeling

Knowledge modeling supports users in formalizing and documenting knowledge elements acquired for development of knowledge-based systems. Hao, Yan, Wang, Gong & Lin (2013) developed a knowledge reuse model to promote the level of reusing the accumulated design knowledge in the company. The design knowledge reuse patterns were identified which contributed to the understanding of how designers reuse knowledge during the design process. An ontology model of knowledge, based on the unified description framework, was proposed by Xiayi, Hu, Xudong & Mu (2013). Firstly, the formats of representation for all kinds of knowledge in aircraft design knowledge were studied, and then a unified description framework for this knowledge was proposed. Liutvinavičius & Lopata (2015) analyzed the techniques for system dynamics and decision-making process modeling.

Ouali, Mhiri & Bouzguenda (2016) proposed a multidimensional business knowledge model using a set of rules organized around the three-key perspectives of business processes: (i) process perspective, (ii) organizational perspective and (iii) informational perspective. Boshkoska, Liu & Chen (2018) proposed framework for development of a decision support system for evaluation of the knowledge boundaries in agricultural value chain. It is a two-step approach based on OntoGen tool, used for generation of an ontology for knowledge boundaries, and the DEXi tool, used for expert modelling and preparation of the DSS for evaluation of the knowledge management boundaries. In order to get the optimized result in skill-based e-learning, a fuzzy knowledge model was applied by Gomathi & Rajamani (2018). The combinations of framed rules were used to acquire the knowledge. Konys (2018) provided formal, practical and technological guidance to a knowledge management-based approach to sustainability assessment. The author proposed ontology as a form of knowledge conceptualization.

Ontology

Ontology is an explicit specification of conceptualization. It is a formal representation of the knowledge by a set of concepts within a domain and the relationships between those concepts. Zhou (2007); Turki, Kassel, Saad, & Gargouri (2014); and Feilmayr & Wöß (2016) provided a comprehensive review and discussion of major issues, challenges, and opportunities in ontology learning.

Chandramouli, Arguedas & Izquierdo (2013) presented surveillance ontology to translate the high-level linguistic rules into the information that can be processed and used to assess the compliance of the video analysis module with the rules defined. Li, Xu, Zhang & Lau (2014) illustrated an ontology-based Web mining framework to improve the accuracy of unemployment rate prediction. Ghanem, Mouloudi & Mourchid (2015) proposed ontology of scientific research, and an approach for populating it from websites of scientific publishers, to get a knowledge base for all disciplines, and keep it updated. Paredes-Valverde, Rodríguez-García, Ruiz-Martínez, Valencia-García & Alor-Hernández (2015) presented an ontology-based information retrieval system for DBpedia called Ontology-based Natural Language Interface. This model allows inferring the answer type expected by the user through an established question's classification. Fan, Hua, Storey & Zhao (2016) developed a process ontology based approach to resolve semantic ambiguity in business. The approach is based on cognitive load theory and is intended to reduce semantic ambiguity by avoiding construct overload and construct redundancy. Ghorbel et al. (2016) presented a user-friendly tool, MEMO GRAPH, for visualizing and navigating ontologies. MEMO GRAPH provides an accessible and understandable user interface that follows the *design-for-all* philosophy.

Andrés, Arvor, Mougenot, Libourel & Durieux (2017) implemented an ontology-based prototype to automatically classify Landsat images based on explicit spectral rules. The ontology was designed to achieve a generic and versatile representation of concepts in remote sensing. Lee, Lee & Kwan (2017) proposed a location-based service using ontology-based semantic queries with a focus on the indoor activities in a university context. University activity ontology model was designed for sharing, managing

and querying data semantically. In order to improve the efficiency of knowledge of coal mining equipments, Zhang, Wang, Li & Jiang (2017) proposed a knowledge modeling method based on ontology. The ontology model of coal mining equipment was built with the help of Protégé. Ahmadinia, Movaghar & Rahmani (2018) modeled physical entities, information of which is collected by sensor networks. An ontology is presented for semantically modelling physical entities in the real world, and a method was proposed for extracting the semantic information of entities from the data collected based on the presented model. An & Park (2018) proposed a methodology to automatically generate ontologies and manage the OWL individual through an interaction of the database and the ontology. Authors described the automatic ontology generation process with example schema and demonstrated its effectiveness by comparing it with existing ontologies using the ontology quality score.Cedeno-Moreno & Vargas-Lombardo (2018) created a methodology to extract the necessary elements from a text written in natural language using natural language processing tools for specialists using ontology.

Katis, Kondylakis, Agathangelos & Vassilakis (2018) presented the methodology and the development process of an educational ontology that can be reused and applied to any type of course in different institutions and contribute to several curriculum tasks and course activities. Küçük & Küçük (2018) presented an improved and extended version of a wind energy ontology. The ontology is enriched with new concepts, crisp/fuzzy attributes, and instances to increase its usability in semantic applications regarding wind energy and is utilized within a Web-based semantic portal application for wind energy. Rodríguez-García & Hoehndorf (2018) developed the Onto2Graph conversion algorithm to convert ontologies into graphs efficiently. Shi & Weninger (2018) presented a preliminary approach using concept ontology for extracting and visualizing group discourse by adapting Wikipedia's category hierarchy to be external concept ontology. Teymourlouie, Zaeri, Nematbakhsh, Thimm & Staab (2018) exploited contextual knowledge to detect hidden errors and demonstrated that adding general ontologies like DBpedia as contextual knowledge in the ontology debugging process results in detecting contradictions in ontologies that are coherent.

Knowledge Visualization

Knowledge Visualization is a relatively new field of research that focuses on the creation and transfer of knowledge by visualizations preferably with the help of computers. The area of Knowledge visualization develops cutting-edge visualization methods for analyzing large amounts of data and helps users understand complex relationships between them.

Bresciani & Eppler (2013) proposed a framework for the use of knowledge visualization in the creation and development of social enterprises and posited that each phase of the social venturing process requires a different knowledge visualization method. Brynne, Bresell & Sjögren (2013) described effective visualization of integrating preclinical and clinical data using a project-centric approach. Eppler & Pfister (2013) studied hybrid knowledge visualization in police crime fighting and military operations, and examined the knowledge visualization practices of a leading regional police force (and of a military unit) to derive insights for corporate knowledge management. Boehnert (2017) contributed to a theory of knowledge visualization and presented two discourse mapping projects on environmental themes: mapping climate communication and mapping degrowth. Ursyn (2018) introduced basic visualization concepts and discussed several related issues including metaphors in visualization, bio-inspired applications and apps, and many more. Zou, Yue & Le Vu (2018) performed visualization and analysis conducted a systematic analysis of the road safety studies of the mapping knowledge domain software tools VOSviewer and Sci2 Tool.

Semantic Networks

A semantic network is a knowledge base that represents semantic relations between concepts in a network. Bessmertny (2010) studied the concepts of knowledge visualization based on semantic networks. Drieger (2013) developed a method for visual text analytics to support knowledge building, analytical reasoning and explorative analysis by using semantic network models that are automatically retrieved from

unstructured text data. Hussain, Latif, Rextin, Hayat & Alam (2014) presented a novel approach for scalable visualization of semantic nets using power-law graphs. Kenett, Anaki & Faust (2014) implemented a novel computational approach to the study of semantic networks, through the analysis of free associations. Li & Xiao (2014) discussed a relational model of semantic networks and a two-dimensional storage structure of relational data table based on the semantic network knowledge with practical examples. Ha et al. (2015) described semantic network visualization by using sentiment words of movie review data, and suggested a clustering of nodes by connecting the sentiment words map and social network.

Dudycz (2017) presented selected practical application aspects of the semantic network visualization in support of decision-making processes in the narrow context of financial indicators analysis. Jégou, Drozdzal, Vazquez, Romero & Bengio (2017) extended DenseNets to deal with the problem of semantic segmentation. The authors concluded that the model has much less parameters than currently published best entries for these datasets. Kim, Yoo, Lee & Seo (2017) tracked the trends of academic research on Internet of Things by examining Web of Science database using semantic network analysis. Sugandhi & Mahajan (2017) discussed the semantic network approach to identify affects in natural language input and focuses on representing spatiotemporal affect information.

Semantic network analysis was performed by Jiang, Anderton, Ronald & Barnett (2018) to characterize the presentation of the genetically modified organism, a proxy for food developed from genetically engineered crops, on the web. Texts from three sources were analyzed: U.S. federal websites, top pages from a Google search, and online news titles. Leal (2018) provided a precise definition both of antigraphs and of the mapping of semantic graphs into antigraphs. A web application to visualize and interact with these diagrams was implemented to validate the proposed approach. Mai, Janowicz, Prasad & Yan (2018) discussed an approach for semantically enriched geospatial data visualization and searching framework. The resulting map, as a representation of the semantic distribution of these geographic features, was produced by using multiple techniques including paragraph vector and clustering. Russell & Reimer (2018) introduced two

criteria of argument quality—attribute degree centrality and attribute tie strength. Analyses of semantic network data collected on over-the-ear headphones attributes from the environment and cognitive representations are reported. Wojcik (2018) highlighted advances in the understanding of how the early lexical–semantic system is structured, showing that during word learning, toddlers encode connections between words, which are then leveraged for further learning and more efficient processing. Yanagisawa (2018) proposed a multilingual semantic networks framework which is a graph where multiple language words, as nodes, are semantically linked through concepts. The author implemented Word Net of English, Japanese, and French into a graph database as a multilingual semantic networks framework.

Motivation

The above literature review revealed that:

1. *Knowledge management is becoming a commercial necessity for many organizations, in order to manage their intellectual assets and gain competitive advantage. It has the potential of enabling businesses to gain competitive advantage (Abdullah, Benest, Evans & Kimble, 2002; Alyoubi, 2015).*

   Knowledge management provides the mechanisms for systematically managing the knowledge that evolves with the organization. It is infiltrating every aspect of an organization (decision-making, product development, human resourcing, customer relationships, and supply chain) to improve business efficiency, and thus there is a need to develop new tools for enhancing knowledge management.

2. *DSSs are viewed as key support functions, because they enable knowledge operatives and decision-makers to make well informed decisions through effective study of semi- and ill-structured variables in the external environmental factors (Alyoubi, 2015).*

   DSSs have evolved from concepts of management information systems to indispensable information systems that aid for decision-making. Organizations need to recognize the relationship between the decision making process and knowledge management. This recognition could enhance their decision

making capabilities. Thus synergy of DSSs with knowledge management will enable businesses to arrive at a more informed and scientific decision.

3. *In order to make intelligent decision, the data has to be transformed, harmonized and processed both statistically and analytically. The potential increase in databases makes this analysis more complex with the use of classical statistics procedures as very limited information and knowledge can be gleamed (Serapião & Bannwart, 2013).*

   In recent years, an enormous development in the area of complex data analysis has been made with data mining. Knowledge modeling tools are thus needed to enhance knowledge management and its three associated processes: i.e., tacit to explicit knowledge conversion, explicit knowledge leveraging, and explicit knowledge conversion.

4. *The effectiveness of knowledge acquisition tools depends on appropriate preparation of data and interpretation of the results, which are difficult tasks when dealing with heterogeneous, distributed data from multiple sources (Bernstein, Provost & Hill, 2005).*

   Therefore these tools can be integrated with ontologies to create a semi-automatic knowledge discovery cycle for the extraction of further knowledge. Ontology-based information retrieval, aim at improving the interface between data and search requests in order to bring the result sets closer to the users' research requirements.

PROPOSED WORK

In the view of the above discussion, the focus of this research study is to develop hybrid knowledge modeling tools for making smart decisions.

The Objectives of the research study

1. Design and development of a DSS and integrating it with knowledge management system;
2. Design of intelligent database infrastructure;
3. Development of hybrid knowledge modeling and visualization tools; and
4. Generation of Knowledge Warehouse.

Methodology to achieve the objectives

1. *Development of a DSS and integrating it with knowledge management system*

   This research study will be devoted to develop a DSS with the basic components: database management system, model-base management system and a user interface, as well as additional component(s) for assisting decision makers in accomplishing their organizational objectives. The proposed architecture of the system is shown in Figure 4.

   The database management system will manage spatial and non-spatial data, model-base management system will provide analytical facilities and intelligence to the system, and the user interface will facilitate interaction of decision maker with the system.

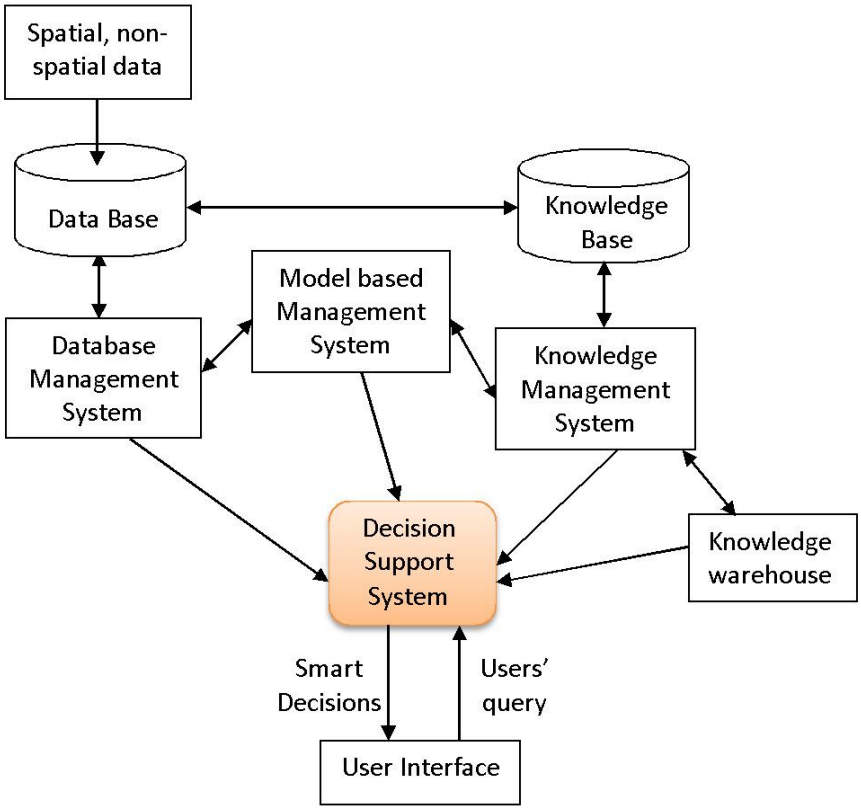

Figure 4: Architecture of the proposed system

2. *Design of intelligent database infrastructure*

This study will deal with the variables like performance, time, location, and others based on the application area chosen for the study. The multi-databases considered in this study will be Object-relational database, or Spatial and temporal data, on the basis of suitability of the data.

The data will be collected for supporting smart decisions from primary and secondary sources. This includes finding out what data is available, obtaining necessary data, and then integrating all the data into one data set, including the attributes that will be considered for the process.

One way to make data access and manipulation in large, complex databases simple and more efficient is to integrate database management systems with knowledge processing capabilities. Intelligent

database infrastructure will be created which will feature query optimization, intelligent search, and the possibility of making automatic discoveries.

The application domain for this study will be one of the following (depending on the availability of the data):

a. Generating smart decisions in the field of higher education (taking Dayalbagh Educational Institute (Deemed University), Agra as a case study);
b. Generating smart decisions in the field of environment conservation (taking Agra as a case study); or
c. Generating smart decisions in the field of healthcare (taking Agra as a case study).

3. *Development of hybrid knowledge modeling and visualization tools*

Techniques like data mining, ontology, multi-criteria decision making, and/or case based reasoning will be integrated for effective knowledge modeling to provide smart decisions.

4. *Generation of Knowledge Warehouse*

The knowledge warehouse will consist of knowledge management system which will integrate the knowledge base, model base and the analysis tasks. In order to develop knowledge warehouse a semantic based approach will be used. The main idea behind this this will be to extract and use knowledge form the data.

The developed knowledge warehouse will provide the decision maker with an intelligent analysis platform that will enhance all phases of the knowledge management process. Intelligent analysis platform will provide array of hybrid knowledge modeling and analysis tools.

Stages of developing the proposed system

The system will be designed and developed using the component based software development process model. Different workflows will be performed over the entire life cycle. The core workflows will include (Figure 5):

1. **Requirements Workflow:**

   This step includes identifying business requirements and acquiring the basic understanding of the application domain.

   The priorities will be established depending on the relative importance of the identified requirements. This priority list will be used to establish the subsequent iterations of system development. The Constraints (like *deadlines, existing hardware, software*) will also be identified in this phase.

2. **Analysis Workflow:**

   On the basis of the established priorities, the identified requirements will be analyzed and refined for detailed understanding. Specifications will be produced for testing. Conceptual model of the system will be developed using UML diagrams and descriptions.

3. **Design Workflow:**

   Analysis artifacts will be refined so that these can be implemented. The relevant data will be collected from primary and secondary sources. Intelligent database infrastructure will be created by defining the metadata, and updating the data source to include all the information necessary for the implementation.

   Knowledge ware house will be designed as an *information repository* in which knowledge components will be cataloged and stored for reuse. The knowledge warehouse will also support ad hoc queries and intelligent help.

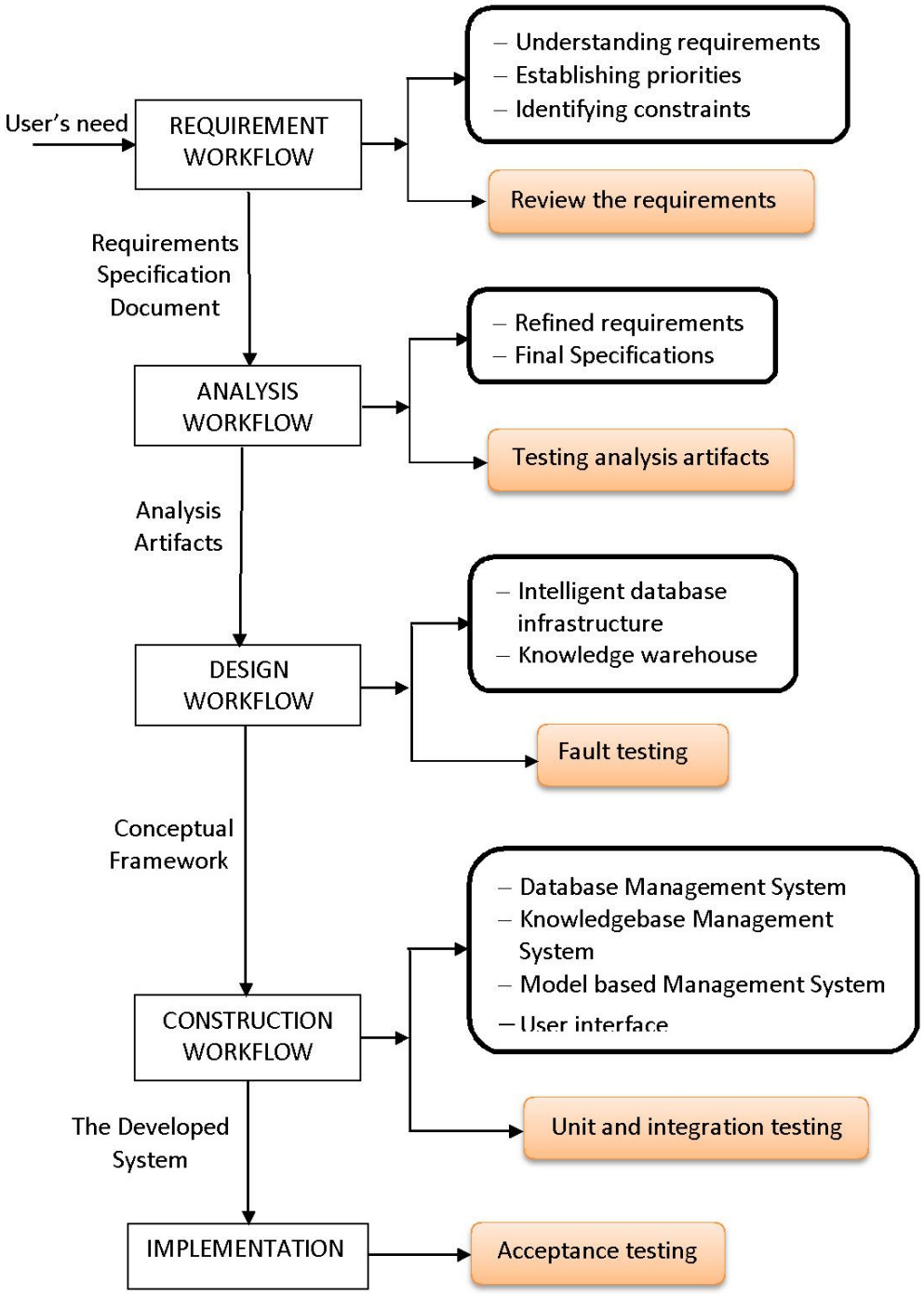

Figure 5: Stages of development

4. Construction Workflow:

According to the requirements, models and algorithms will be developed, and will be stored in models database. The system will be implemented in Visual Basic or .NET environment.

5. Test Workflow:

Testing will be carried out in parallel with all other workflows:

- Requirements will be reviewed;
- Design will be tested for logic faults, interface faults, error handling, and conformance to specifications;
- Finally unit testing, integration testing, and acceptance testing will be performed.

The proposed system will support smart decisions which are critical for achieving and sustaining organizational excellence. The knowledge management component of the system will help decision makers focus on organizational objectives such as improved performance, competitive advantage, innovation, and continuous improvement of the organization. The analytical tools will help in increasing productivity, efficiency, and effectiveness and gives many businesses a comparative advantage over their competitors, allowing them to make optimal choices for technological processes and their parameters, planning business operations, logistics, or investments.

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